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Interactive Visualization of Muscle Activity During Limb Movements : Towards Enhanced Anatomy Learning

Armelle Bauer^{1,2,3}, Florent Paclet⁴, Violaine Cahouet⁴, Ali-Hamadi Dicko^{1,2,5},
Olivier Palombi^{1,6}, François Faure^{1,2,5}, Jocelyne Troccaz^{3,5}

¹INRIA, ²LJK-CNRS, ³TIMC-IMAG, ⁴GIPSA-lab, ⁵Univ. Grenoble Alpes, ⁶LADAF



Figure 1: Interactive display of muscle activations during knee flexion. Left: a user moving in front of the Kinect sensor. Middle: activation displayed on action lines. Right: display on 3D meshes.

Abstract

We propose a framework to investigate a new way to learn musculoskeletal anatomical kinetics using interactive motion capture and visualization. It can be used to facilitate the learning of anatomy by medicine and sports students, and for the general public to discover human anatomy in action. We illustrate our approach using the example of knee flexion and extension by visualizing the knee muscle activation prediction with agonist and antagonist co-contraction.

Muscle activation data for specified movements is first measured during a preliminary phase. The user is then tracked in real time, and its motion is analyzed to recognize the motion being performed. This is used to efficiently evaluate muscle activation by interpolating the activation data stored in tables. The visual feedback consists of a user-specific 3D avatar created by deforming a reference model and animated using the tracking. Muscle activation is visualized using colored lines of action or 3D meshes.

This work was made possible by the collaboration of three complementary labs specialized in computer-aided medical intervention, computer graphics and biomechanics.

Keywords : Anatomy Learning, Biomechanical Simulation, Real-Time, Augmented Reality, Embodiment, Motion Capture and Reconstruction

1. Introduction

Learning functional anatomy and understanding anatomical kinematics is important for medical studies, sport education as well as for education more generally. However, this learning process remains tedious and difficult due to the complex-

ity of the domain which includes a large amount of structured, static and dynamic notions. Understanding the musculoskeletal system and its mobility usually requires 3D visuo-spatial abilities [HCD*14,HCR*09]. An important difficulty comes from the fact that this is still taught using static ob-

jects from books, drawings, photos, or the dissection of cadavers [GCB*07]. With the emergence of new technologies such as 3D modeling and animation, Augmented Reality (AR) systems, *etc.*, new approaches of learning through interactions have been proposed [FBE*13, PR13, KBSC14] to ease the learning process and the construction of mental representations of anatomy. Our work is based on two assumptions :

- Space visualization is fundamental to the understanding and the learning of complex articulated 3D shapes.
- Our motor system influences our cognition (Embodiment theory)

Assuming that the use of one's own body could make the learning process of musculoskeletal biomechanics more efficient led us to sketch the "Living Book of Anatomy" (LBA), an AR system to visualize the relevant anatomical knowledge of the trainee body in action. The key idea is to capture a user action (a limb motion for instance) and to visualize its effect on the internal anatomy within an AR paradigm : for instance, the internal structures are superimposed on the image of the trainee. Developing the LBA requires a novel combination of technologies including motion capture, anatomical knowledge modeling, user-to-model mapping, AR rendering. In this paper, we tackle the challenge of real-time motion capture and muscle activation display using a novel combination of state-of-the-art approaches.

Our biomechanical model is created using an ontology of anatomical structures (MyCorporisFabrica) [PUF*14, DGFP12] connected with a complete set of 3D geometrical model of the human body [BUD*14]. User motion is captured using a *Kinect* sensor associated with standard software and complemented with additional filtering. To avoid intensive, ill-posed inverse dynamics computations, muscle activation is queried in tables based on pose and velocity. Muscles are rendered in real-time as deformed 3D shapes using vertex blending methods, or as colored lines to highlight activation. Our key contribution is the real-time visualization of the human body musculoskeletal system kinetics and muscle activity.

The remainder of the paper is organized as follows. In Section 2, we briefly survey the related work covering medical learning and real-time applications. In Section 3 we then describe in detail the proposed pipeline and the input data we are working on. We present and discuss our results in Section 4. We finally conclude and sketch future work in Section 5.

2. Related Work

Motion capture of the human body has been a subject of great interest in computer graphics, vision, biomechanics, films and medical applications, and force space reasons we can only scratch the surface of this domain. People generally try to use marker-less motion capture systems be-

cause of the lower price and the simple setup [CSC14]. This approach has also gained popularity in the biomechanics community [CSC14, CGMA10, CMC*06]. Our project is based on it in order to provide an application everyone could use easily and at a low cost. Some recent papers analyze motion capture using *Kinect* sensors and compare it with the real motion captured with more sophisticated hardware [Red13, EPnB*13].

A lot of studies were carried on about anatomy learning [DRC*06, PR13, KBSC14, SM08], and 3D models have become increasingly popular [HCD*14, HCR*09, GCB*07]. Augmented reality (AR), which consists in superimposing data on visible objects, has been increasingly used in the medical domain [DHL*02, JBC08, Spe12]. Our project is inspired by the work of Nassir Navab on the Magic Mirror project [FBE*13, BKBN12]. We extend it using biomechanical data related to user motion.

3. Materials and Methods

Our method combines data from three sources:

- Muscle activation data for specified movements, measured during a preliminary phase (Sec.3.1)
- Real-time user motion capture and muscle activation evaluation (Sec.3.2)
- A 3D avatar displayed in the same pose as the user, and highlighting muscle activation (Sec.3.3)

Figure 2 summarizes the pipeline of the method. In this experiment we focus on muscle activation during knee flexion/extension for anatomy learning purpose. We used MyCorporisFabrica [BUD*14] to select the entities (muscles and bones) involved in the knee flexion and extension.

3.1. Measuring activation

To evaluate musculoskeletal movement, a motion capture system is sufficient. However, muscle and/or tendon tension is difficult to evaluate due to redundancies in the musculoskeletal system. Indeed there are more actuators (muscles) than degrees of freedom in joints. This leads to an under-determined system of equations, resulting in an infinity of possible muscular coordination with different synergies and co-contraction patterns to achieve the same task. In this work, motion capture and identification are applied to the flexion-extension of the lower limb, and our goal is to evaluate and display the corresponding muscle activations. To solve the redundancy problem, we use experimental measurement data to feed a biomechanical model of the lower limb based on anatomical and functional knowledge, in order to compute knee muscle activations including agonist and antagonist co-contraction. The acquisition of the knee flexion muscle activation was made only on the right segment of the human body, since the muscle activation should be the same for each leg.

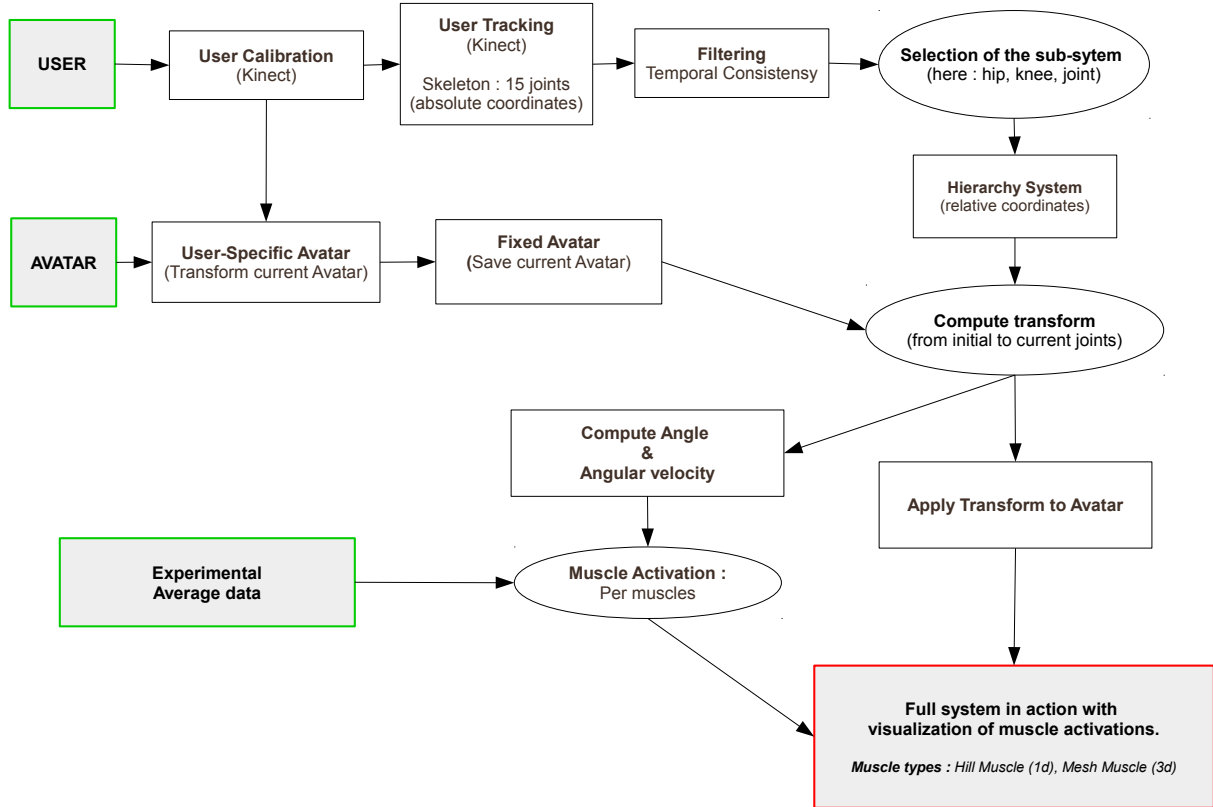


Figure 2: Pipeline of the application.

Database construction An experimental acquisition is performed on a single healthy subject (48yo / 186cm / 77kg) to provide muscle activation patterns corresponding to flexion and extension. The motion capture is performed during squat and no-load lower limb flexion-extensions using 12 Vicon cameras sampled at 250Hz. At the same time, the electromyographic activity of the mono and bi-articular flexor and extensor knee muscles is recorded at 2000 Hz (total 10 muscles) using a Biopac MP150 device.

The subject is standing on a force plate (force plate data not used in this work) and performs right leg flexion/extension cycles either in squat or no-load conditions (see picture 3) at three (low, medium and high) velocities. The subject performs 6 flexion/extension cycles in each condition. Pairs of silver-silver chloride surface electrodes were used to record the raw activity from the 10 main muscles producing the knee torque : Vastus Medialis (vast_med), Vastus Lateralis (vast_lat), Rectus Femoris (rect_fem), Tensor Fasciae Latae (tfl), Sartorius (sartorius), Gracilis (gracilis), Biceps Femoris (bi_fem_lh), Semi Tendinosus (semiten), Gastrocnemius (med_gas and lat_gas). The electrodes are positioned parallel to the muscle fibers

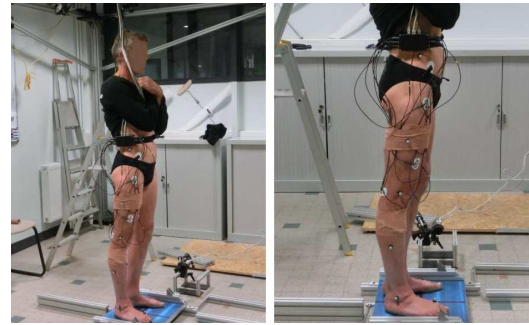


Figure 3: Photos of the experiment.

with an inter-electrode distance of 15mm following careful skin preparation to reduce the skin impedance according to the SENIAM (Surface EMG for Noninvasive Assessment of Muscles) recommendations (www.seniam.org). The electrodes over the lower-limb muscles are placed centrally over the muscle bellies following palpation of a resisted isomet-

ric contraction. The ground electrode is placed over the right iliac crest in front of the ilium bone.

Data analysis The Y and Z lateral displacements of each marker are filtered using a fourth-order Butterworth filter with zero phase lag and a cut-off frequency of 4 Hz. Inter-segmental angles are calculated at ankle, knee and hip joints according to the convention shown in Figure 4.

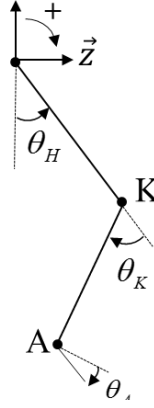


Figure 4: Three-link model of the lower limb.

The derivatives of angular position are calculated at each time t using a centred finite difference scheme. Finally, kinematic values are averaged to give a mean cycle for each condition (Figure 5).

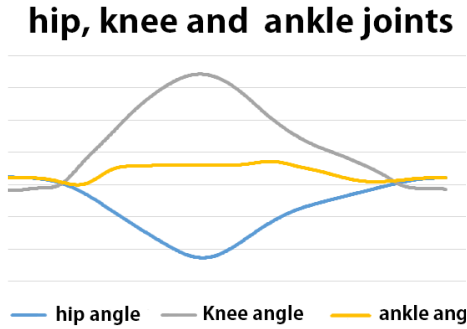


Figure 5: Hip, knee and ankle angles (rad) evolution during a mean cycle.

The data is first demeaned then filtered using a Butterworth filter (4th order, band pass 20-450Hz) with no lag essentially to remove movement artefacts. RMS is calculated using a 250ms sliding window with overlapping to get the envelope of the EMG signal. RMS values is normalized using Maximal RMS value (RMSmax) detected across all trials

for each muscle i :

$$\overline{RMS}_i(t) = \frac{RMS_i(t)}{RMS_{max_i}}$$

Finally the normalized RMS signal is averaged to provide a mean cycle for each condition, and is filtered using a Butterworth filter (4th order, low pass 4Hz) with no lag to obtain an activation coefficient a_i for each knee muscle. The activation of deep muscles (Biceps femoris: short head (bi_fem_short), semimembranosus (semimemb), vastus intermedius (vast_int)), which EMG activities cannot be measured using surface electrodes, is estimated using synergist neighbor muscles. This data can then be used to provide suit-

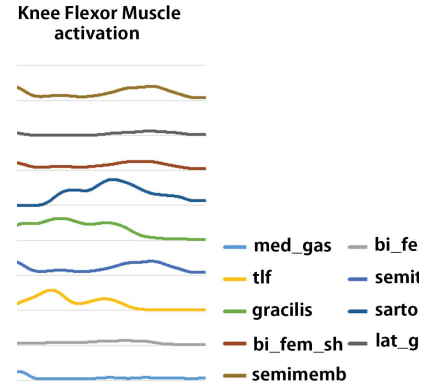


Figure 6: Activation coefficient of knee flexor muscles during a mean cycle.

able information for anatomical structures animation in the LBA.

3.2. Motion capture

We use a *Kinect* with NiTE and the OpenNI SDK [Ope] to track the user actions. The process starts with a calibration (Sec.3.2.1). We then enter the main application loop. At each time, the user tracking provides us with joint angles (Sec.3.2.2), and the motion is analyzed (Sec.3.2.3).

3.2.1. Calibration

In the process of *Kinect* calibration we find the subject parameters and we transform a reference 3D anatomical avatar to match the user in the learning environment. We use the T-pose (3D avatar and *Kinect* initial position) to calibrate the user. Figure 7 illustrates the skeleton used for the initialization.

NiTE provides a user bounding box which we use to find two anthropometric values : the user breadth (width of the bounding box) and the user height [ECA14]. Based on the user and avatar breadth and height we compute the width and height scale factors. To get the third dimension (depth)

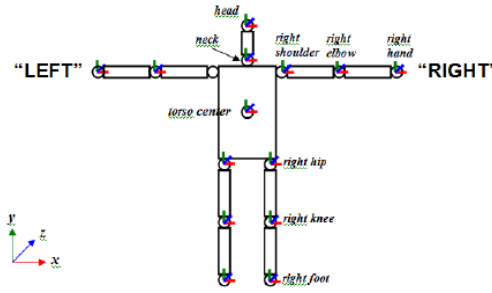


Figure 7: NiTE tracking skeleton (15 bones).

we use a ratio between the width and height scale factors. Using these scale factors we find the transformation matrix to deform the reference avatar to fit the user global size, as illustrated in Figure 8.

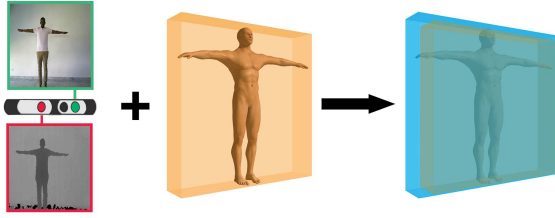


Figure 8: user-specific calibration (user, reference avatar, user-specific avatar)

3.2.2. Tracking

After the calibration we compute smooth rotation interpolations between the frames, while maintaining the distances between the joints. We only take into account the joints needed to control our system : hip joint, knee joint and foot joint.

NiTE re-computes skeleton joints at each frame based on the depth image. Unfortunately, the *Kinect* sensor offers an imprecise depth image which leads to limits in precision for the skeleton joints. To avoid inconsistencies during the tracking we save the initial skeleton at initialization time, and we enforce constant distance constraints between the joints during the tracking. Before applying our hierarchical model, we smooth the individual bone trajectories using a 5x5 convolution matrix. The filter is coupled with Dual-quaternion Linear Blending [Ken12, KCZO07] for multiple rotation interpolations. Each joint is composed of a position (3D vector) and an orientation (quaternion). We separate the joint positions and orientations to take only into account the joint rotations in the hierarchical joint model. This results in smooth rotation interpolations between frames and avoids jiggle effects.

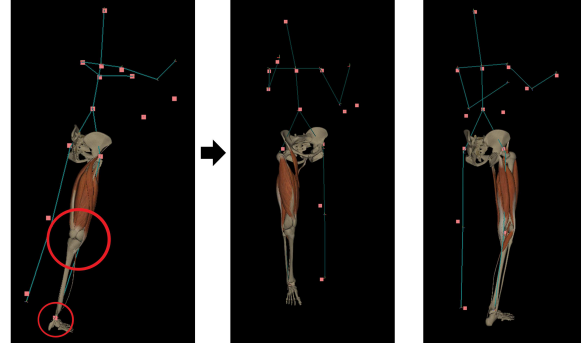


Figure 9: on the left skeleton tracking without filter, on the right skeleton tracking with filter

3.2.3. Motion analysis

To avoid complex inverse dynamics computations, the muscle activations are retrieved from recorded data, based on joint angles and velocities. To fit our experimental data (Sec.3.1) we have to compute the angle and velocity of the tracked user as well. The current version considers only the hip. To compute the user angle we transform the hip quaternion to Euler angles and we peek the angle related to the x axis. The angular velocity is computed using finite differences.

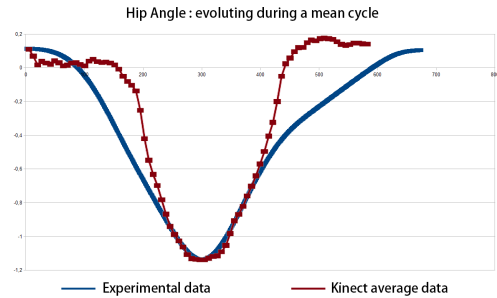


Figure 10: experiment and Kinect : hip angle (rad) evolution during a mean cycle (flexion/extension)

The angular velocity is negative during flexion and positive during extension. Thus based on the angular velocity we know if the user is performing flexion or extension. Then, we use the hip angle to find activation per muscle using a linear interpolation of the experimental data. In the current version, we do not consider the value of the velocity.

3.3. Motion and activation visualization

The mapping from the user to the model/avatar is performed by attaching bones and muscles to the skeleton using Linear

Blend Skinning. The muscles can be visualized in two ways: 1D muscles (muscle line of action) [The03] and 3D muscles.

- 1D (line of action) Hill muscles : to see all muscles behaviors (even underneath muscles like the "vastus intermedius"). Using anatomy transfer [AHLG*13], we adapt the muscles of the OpenSim [AWLD10, DAA*07] model to our system.
- 3D muscle meshes : for more realistic muscles visualization. Our 3D anatomy avatar provides meshes of lower limb muscles.

We display muscle activation using a smooth color map from blue (no activation) to red (maximum activation). In theory, muscle activation is a percentage value between 0.0 and 1.0. To better highlight muscle activations, we choose to use the "experimental" maximum instead of "theoretical" maximum to 1.0. For a complete visualization we display all the lower limb entities. Figure 12 shows the visualization (1D and 3D muscles activation) for 4 of our users. More results are in the video attached.

4. Results and discussion

Our framework is implemented in C++ and runs on a commodity laptop PC. The real-time capture and activation display run at 25 Hz, with a lag of less than 0.1 s. The visual feedback is currently performed on the screen of the PC, as shown in the accompanying video.

The motion sequences were acquired for 6 young adult men with an average height of 1.81m, an average of weight of 85.3kg, and 4 young adult women with an average height of 1.60m and an average weight of 55.7kg. All of them without any type of injury or physical incapacity in their extremities. To get uniform results we work with *Kinect* sequences made in the same room and with the same lighting conditions.

Gender	Age	Height	Weight
F	27	1.59	48
F	23	1.60	50
F	24	1.60	58
F	31	1.63	67
H	30	1.72	74
H	27	1.76	110
H	29	1.82	80
H	26	1.83	72
H	25	1.85	100
H	24	1.91	76

Table 1: *Kinect* sequence users exact data

Scaling the reference model takes about 4 seconds, then the interactive visualization begins. The user performs flexions and extensions and sees in real-time his/her muscle activations on the screen.

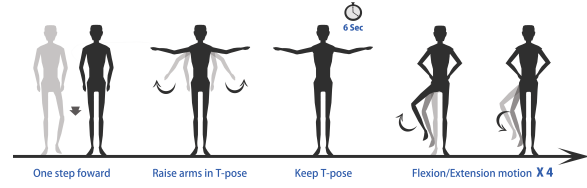


Figure 11: key positions of our sequence from the *Kinect* point of view

We have studied different kinds of flexion-extension movements with various velocities and loading conditions to create a set (library) of averaged lower limb movement references to feed the LBA. This library of muscle activation patterns is used to provide the feedback about the knee muscles for functional anatomy learning. In future work, this experimental process will be greatly improved using additional measurements of muscle activation in maximal voluntary contraction situation. Using an isokinetic ergometer, these activations will be related to knee moment level in various isometric, concentric and eccentric contractions. This knowledge will allow us to more accurately normalize EMG signals acquired during flexion-extension movements. Finally, the development of a biomechanical model of the lower limb coupled with inverse dynamics, optimization procedure and EMG information could produce a better muscle tension estimation in all kind of flexion-extension movement.

The *Kinect* sensor provides an imprecise depth image which leads to limits in precision for the skeleton joints. This leads to an approximate motion feedback for the user. A better filtering of the *Kinect* skeleton [WZC12, MCA07], or a completion of depth sensor data are good response to this problem.

Our user calibration is simplistic while the final goal of our project is to provide a really realistic user-specific avatar. Computing our avatar using real-time anatomy transfer [AHLG*13, GRP10] and anthropometric measurements [ECSCUQ14] would be a good alternative. An other alternative would be to combine the *Kinect* skeleton and silhouette [RVHT12, CPLFR13].

5. Conclusion

Our framework is ready to validate the theory of Embodiment. In this paper we presented a first innovative application for the visualization of human body kinetics in real-time, by displaying muscle activation. We believe that with accurate anatomically-based models and realistic motion, learning anatomy will be eased.

The AR visual feedback will soon be implemented. In the

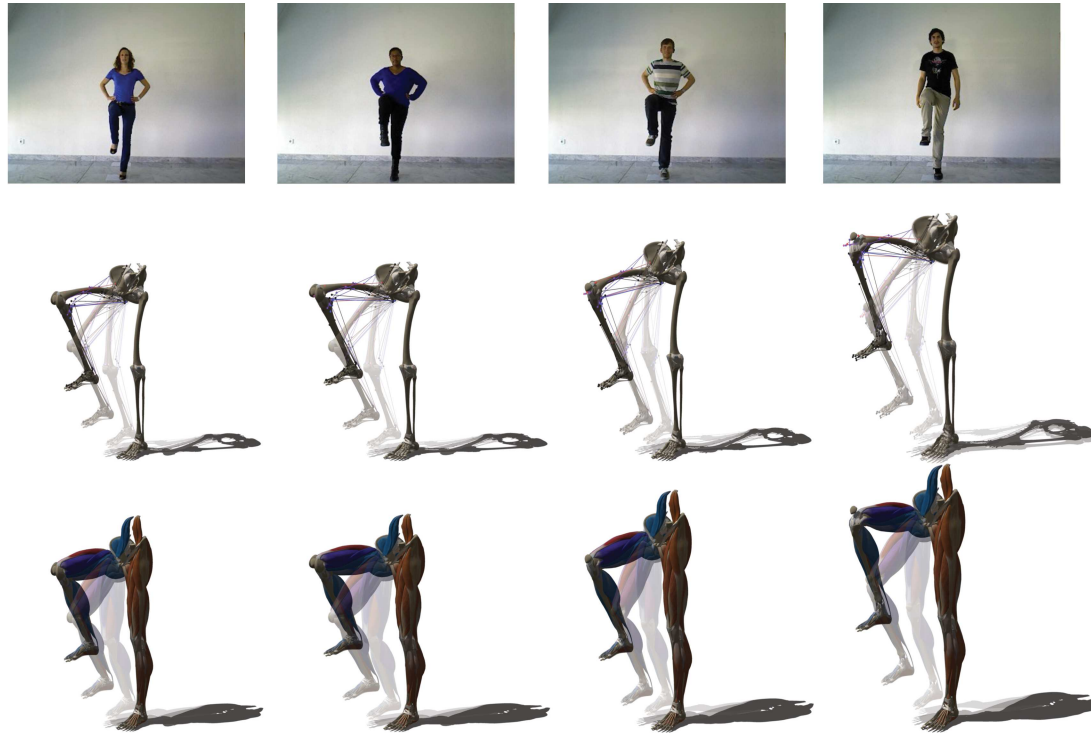


Figure 12: users : color and depth map, 1D muscles visualization, 3D muscles visualization

short term, we want to improve the personalization of the avatar to reinforce embodiment. We also hope to visualize information on other limbs and their motions. In the longer term, we plan to automatically detect the user motion and deliver knowledge accordingly.

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